Inverse Methods in Heat Transfer
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Lecture – 56
Introduction to Week 11 – ANNs as Surrogate Models

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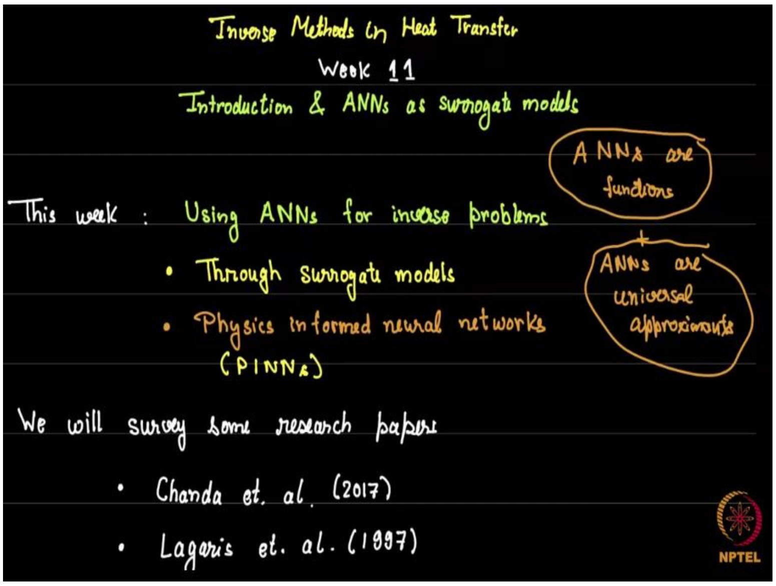

Welcome back, we are in week eleven of inverse methods in heat transfer. In this video I would like you to I would like to give you a simple introduction to this week and also talk specifically about artificial neural networks as surrogate models. Over the last several weeks from week eight to week ten we have been looking at neural networks and we have looked at especially in the last week in detail how the forward pass and the backward pass or the back propagation algorithm works in neural networks.

Now specifically a thing that I would like you to remember as we go through this week is remember that neural networks or artificial neural networks are functions, I emphasize this quite a lot over the last two three weeks but please do remember this especially as we come to this portion the physics informed neural networks portrait okay.

This week what we will be looking at is how to use ANNs for inverse problems and it is this property that helps us do this this plus the fact that ANNs are universal approximative, okay. So what this means is you can write any function you want or you can approximate any function you want as an ANN and in order to find out the parameters of the ANN as we saw in the last three weeks we solve inverse problems.

So, there is a tie up with inverse methods in another fashion house okay. So, this week we are looking at these three things, how to use ANNs as surrogate models which I will discuss in this video. Then we will look at physics informed neural networks which are a way of using ANNs more to solve forward problems as well as inverse problems you will see that when we try to solve ANNs as surrogate models it requires a lot of conventional simulation whereas when you use physics informed neural networks also now known as PINNs physics informed neural networks when we use these you do not need any additional simulation in order to support your inverse problem solution.

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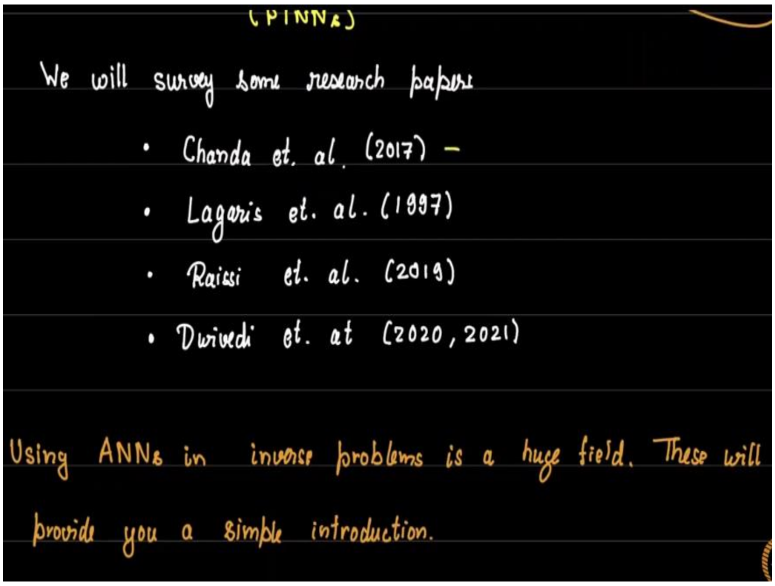

Now we will be surveying primarily this week some research papers I have written those papers down here and I will be showing you some of these papers even in this video. The purpose of these papers is to serve as an introduction to this field okay I would encourage you to go online see if you can download these papers unfortunately, I cannot share these papers directly due to copyright violations.

I will be showing because that is apparently it is not a copyright violation to show and you might have seen online several people do share papers in fact almost all of these papers except for the first one is available freely online on archive. The first paper here corresponds to using ANNs as surrogate models which we look at within this video and these three or four papers are related to using ANNs in order to define physics informed neural networks okay. one last thing before we step into the problems for step into surrogate models this week, I will not be showing you codes I had promised you in the last week that I would show you some of these programs even for last week as well as this week.

This will be doing in the next week this week we will concentrate primarily on theory there were some technical problems because of which I was not able to demonstrate the codes this week. we will stick with theory this week and I will show you some demos and primarily next week's videos will be geared towards showing you demos. So let us now step into the very first problem which is how to use inverse how to use ANNs as surrogate models so let us look at that now.

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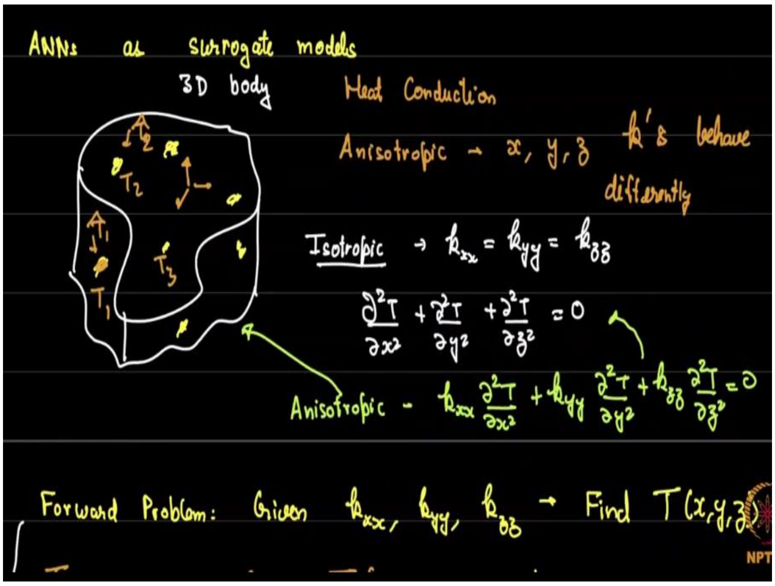

So ANNs as surrogate models what does this mean I will show you by means of an example by reference to the Chanda et al paper. but let us first talk about the general problem and then come back to the specifics. so let us say you have a complicated domain okay complicated let us even say a three-dimensional domain by a domain I mean you have a three-dimensional body okay.

So, there is a three-D body and the inverse problem is as follows, let us say you have let me make the simple let us say we have a heat conduction problem okay so this could this body obviously this is not the shape of any fin within a realistic domain. but let us say I am just showing you a complex enough body so that it does not look like the solution is straightforward so let us take a heat conduction problem let us say within a chip you are trying to optimize thermal management of a chip and you want to optimize heat transfer from there so unfortunately you do not perfectly know the thermal conductivities of the material okay.

So, let us say that the material is what is known as anisotropic. Anisotropic means and this is the paper that I am going to show x y z k behave differently okay so this happens for composite materials some of you might be familiar with this from solid mechanics but in general assume that you have a material which does not behave in the same way in the three coordinate directions that is there are different material properties depending on which direction you are looking at in as far as heat transfer is concerned just as an example or just as clarification, for example if it was isotropic then k in each direction is the same so we would say k_{xx} is the same as k_{yy} is the same as k_{zz} and you would have something like $\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} = 0.$

So, this is if it is isotropic. On the other hand, if it is anisotropic then your property would look like or your governing differential equation coming from energy would look like $k_{xx}\frac{\partial^2 T}{\partial x^2} + k_{yy}\frac{\partial^2 T}{\partial y^2} + k_{zz}\frac{\partial^2 T}{\partial z^2} = 0$. So obviously anisotropic goes to isotropic if $k_{xx} = k_{yy} = k_{zz}$.

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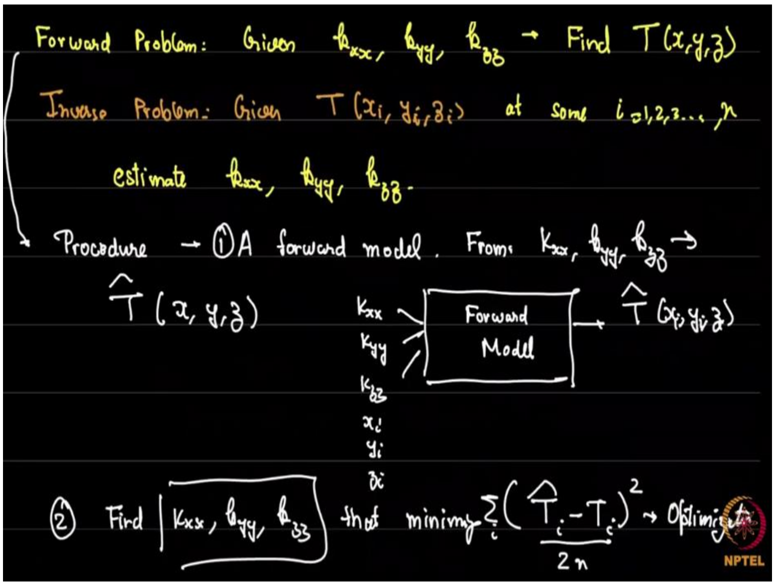

So, in order to solve for temperature within this body here you would have to solve this differential equation. So, this differential equation is what will lead to the solution for temperature c okay now suppose I want to estimate our inverse problem. our forward problem is or let me write the forward problem first.

So, the forward problem would be given k_{xx}, k_{yy}, k_{zz}, find there is a heat transfer or find the temperature distribution find temperature as a function of x, y, z. The inverse problem I will show you the mathematical formulation also little bit later the inverse problem is given t at some locations please remember we can only give this at a finite number of locations for example we could give locations such as this so suppose I have five or six thermal thermocouple sensors distributed across the body even though it looks like it is within a plane remember this is a three d body I could put my sensors anywhere so given this at some x i or some i equal to one two three four how many ever sensors we have we have to estimate we cannot find but we can estimate the property okay.

Now how would one go about this. so the normal procedure will require us to have a forward model what is this forward model forward model solves the forward problem that is from k_{xx}, k_{yy}, k_{zz} find T(x, y, z). okay now this is sort of a black box as we have been doing so you have inputs k_{xx}, k_{yy}, k_{zz} and these three go in into the forward model and what comes out is temperature at any x, y, z that you wish to give if you wish we can add x_i, y_i, z_i here and you get temperature at x_i, y_i, z_i

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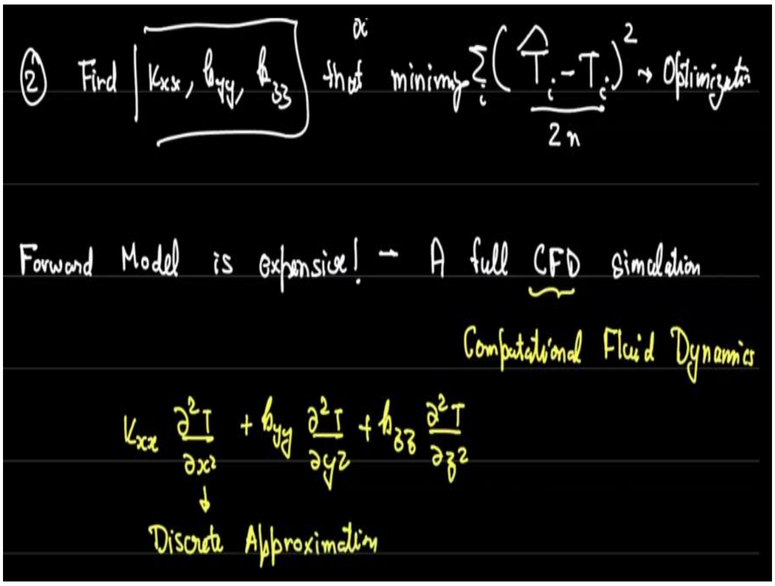

So, the procedure is this you need a forward model then find k_{xx}, k_{yy}, k_{zz} that minimize so let us call this $\hat{T}$ that minimize our $\hat{T}$-T at these points square summed over all I okay so you find the least square loss, you can divide by two and the number of points that we had etcetera okay.

So, we want to find this out and this is an obviously an optimization problem now if you remember all the hand-based calculations that we did this is where they become important each forward calculation takes some effort of course we took linear examples or a simple $a(1\text{-}e^{-bt})$

or some such example but the forward model for this 3D case is extremely complex. So, unfortunately, the forward model is expensive. why is it expensive? because it requires a full CFD simulation. now since I have not talked about CFD within this course I will give you a small very brief introduction to what CFD is. CFD of course stands for those of your familiar computational fluid Dynamics or of course you can have CFD computational heat transfer if you wish.

But the standard name has always been computational fluid dynamics. Idea is simple idea is if you have an equation like $k_{xx}\frac{\partial^2 T}{\partial x^2} + k_{yy}\frac{\partial^2 T}{\partial y^2} + k_{zz}\frac{\partial^2 T}{\partial z^2}$ all these are replaced by discrete approximations. what is the example of a discrete approximation?

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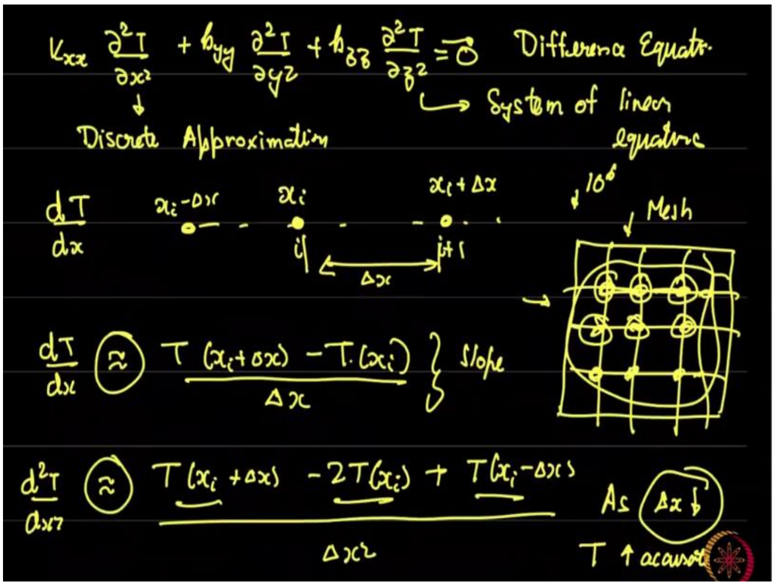

So, the idea is simple if you have two points let us say we are looking at a simple one-dimensional derivative $\frac{dT}{dx}$ then since we have only information at finite number of points let us say this is at x_i this is at $x_i + \Delta x$ then you will say that $\frac{dT}{dx}$ is approximately $\frac{T(x_i+\Delta x)-T(x_i)}{\Delta x}$.

Now what this enable is that this whole equation which is complicated differential equation. now becomes a difference equation for example we can show I am not showing this here that d square t dx square so this of course is just the slope similarly $\frac{d^2T}{dx^2}$ can be approximated by $\frac{T(x_i+\Delta x)-2T(x_i)+T(x_i-\Delta x)}{\Delta x^2}$. So, this is of course approximate please remember this this is not exact. now once you do this this system basically becomes a system of linear equations. why? because all you will have been T at some point minus T at some other point plus T at some other point it is just a combination of temperatures at a lot of places okay.

So, if you see here typically what you would do is let us say your domain looked something like this. you would put these grid points and you will start estimating temperatures here, but every temperature depends on every other temperature, because the equations here you will basically say that this is equal to zero so you will get a series of equations. I will leave I am giving you just a brief idea here for intuition otherwise please look up something called the finite difference method which is the most intuitive method for computational fluid dynamics. you should be able to understand it in case this brief two-to-three-minute introduction was not sufficient. So, what you do is you create what is known as a mesh.

Mesh consists of points where you wish to find out the temperature and as you reduce delta x your estimate T becomes more accurate okay. all this is to say that this forward model is expensive. why is that? because first you will have to create a mesh next you will have to solve for temperature at all points, why because, only when delta x becomes very small your act your solution accuracy becomes very high once you do that usually sometimes you might have as many as million points even if you have ten sensors here in order to solve for the temperature there accurately from your forward model you might require a million mesh points in order to obtain them okay so let us say you have these sensors at all these points you have ground truths T_1, T_2, T_3, etcetera.

You also want to make predictions from your computation even $\widehat{T_1}$, $\widehat{T_2}$ etcetera but in order to calculate $\widehat{T_1}$, $\widehat{T_2}$ you have to solve CFD for every iteration if you are using an iterative method and if it is a nonlinear problem as it was with gauss newton etcetera. you will have to solve for each iteration of gauss newton you will have to solve multiple you have and you need a CFD solution in order to get $\hat{T}$.

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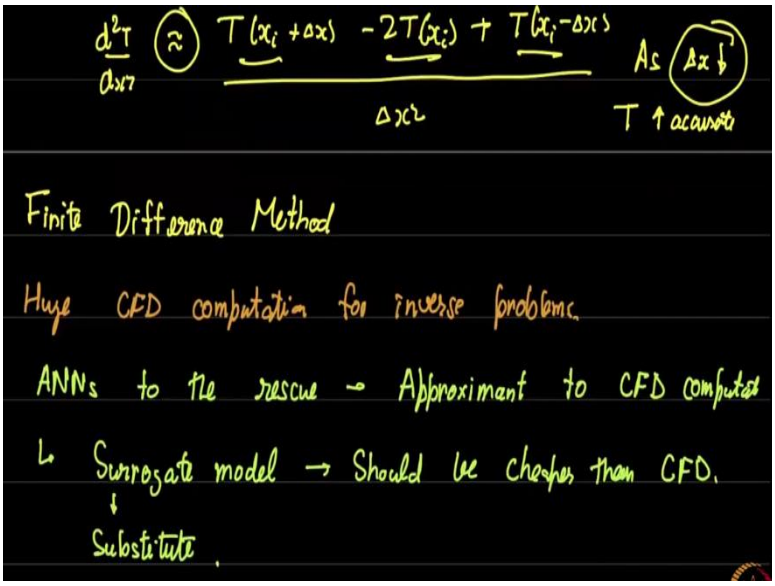

Since this is expensive you cannot really use this in order to solve k_{xx}, k_{yy}, k_{zz} because you have multiple iterations it takes a huge number of CFD simulations for an inverse problem so huge CFD computation for inverse problems. If time permits, I will show you an example of this in the next week but I am not sure if there will be sufficient time for that okay.

Now here is where ANNs come to our rescue okay so ANNs to the rescue how so you use and approximate solution to the CFD computation okay. Now how can we do this the idea is like this so this is what is known as a surrogate or a substitute model. A surrogate means a substitute. So, the idea is this surrogate model should be cheaper than CFD okay. So how do we solve the inverse problem assume that we have some method of getting this okay, assume we get some method of getting the surrogate model then what we do is we use the cheaper model here, you run a forward model but you do not run CFD you actually run the cheaper model and then iterate.

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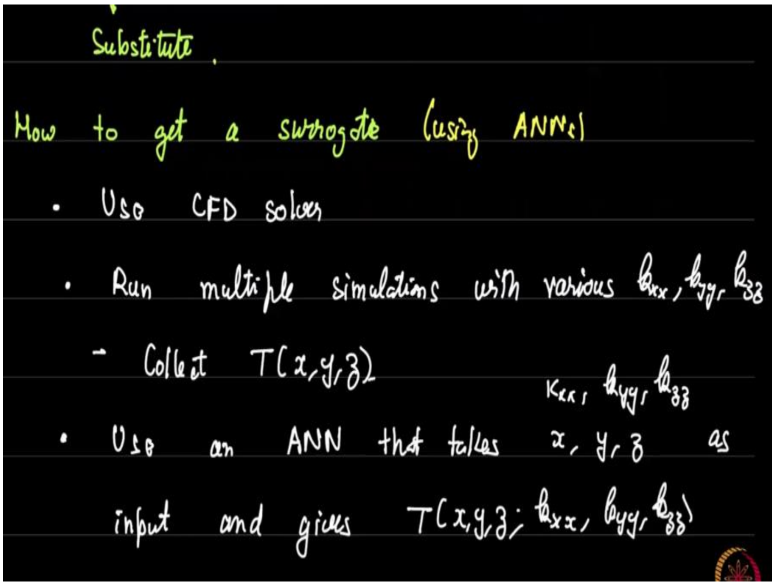

So, let me first show you how to get a surrogate and this is where all that we did in the last few weeks comes to use. So how to get a surrogate using ANNs. so let us say we have used CFD solver run multiple simulations okay so we run multiple simulations with various k_{xx}, k_{yy}, k_{zz}. So, you put a whole bunch of k_{xx}, k_{yy}, k_{zz} collect one second collect T of some x y z at various points and then use an ANN that takes k_{xx}, k_{yy}, k_{zz}, x, y, z as input and gives T of x, y, z with k_{xx}, k_{yy}, k_{zz} as parameters okay

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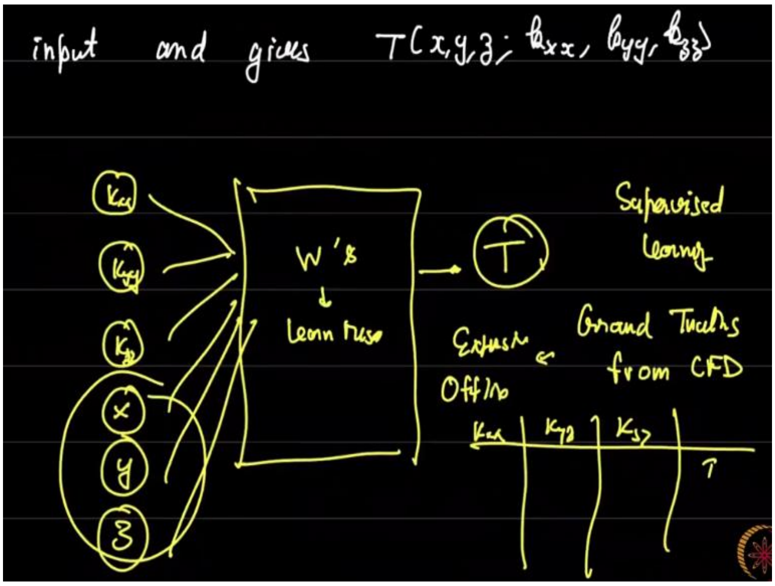

So, in short, your network is going to look like this it is going to look like k_{xx}, k_{yy}, k_{zz}, x, y, z. how many ever layers you want it would be one layer two layers multiple layers and it gives out one output which is the temperature. so how do we train it we do a simple standard supervised learning.

A supervised learning is such that for a given k_{xx}, k_{yy}, k_{zz} and take multiple locations, you actually just need this do a CFD simulation, from the CFD simulation take ground truths from CFD. So, you make a table fix one k_{xx}, k_{yy}, k_{zz} take multiple x, y, zs measure temperatures there so that you get a huge data set of temperature versus k_{xx}, k_{yy}, k_{zz}, x, y, z now trains the model the unknowns of the model are of course w learn these. Now what happens is this process of collecting the data all this process is of course expensive, but it is offline. Offline means we do not have to do it as we are collecting the experiments you can do them just once you do it once you finish it now, what you will actually have been actual measurements okay.

So now you do the experiment after having done the simulation you build your model you build your ANN model now you make some measurements. you make let us say twenty temperature measurements you see those temperature measurements twenty temperature measurements and then solve an inverse problem. how do you solve the inverse problem guess for k_{xx}, k_{yy}, k_{zz} do a forward pass the forward pass however should not be through CFD but through the ANN which is an approximation it is a good enough approximation. So, if you make a good approximate it will do a forward pass through CFD and I will demonstrate it to you next week for some of the simple problems that we have done earlier.

So you do a forward pass through the CFD and through that forward pass you see well how much does T match $\hat{T}$. $\hat{T}$ is remembered through the ANN through the surrogate model T was through the experiment we are making an experiment and trying to match this. once you do that you will see T-hat does not match go back correct k_{xx}, k_{yy}, k_{zz} and keep on doing so note that there are two inverse problems being solved here first inverse problem being solved is to approximate the CFD solutions and find w for the surrogate model. The second approximate so this is for example this inverse problem is for the computation or for the forward model and the next approximate is for the inverse model. Now let me clarify this in case this is not clear let me clarify this by visiting the paper by Chanda et at and hopefully this will become a little bit clearer.

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Estimation of principal thermal conductivities of layered honeycomb composites using ANN–GA based inverse technique

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ABSTRACT

Composite materials are novel inventions of material science which are often used as viable solutions in many technologically challenging situations like aero-space and satellite applications, because of their well known superior mechanical properties. The challenge which these materials always pose to the thermal designers, is knowledge of their thermal properties, effective directional thermal conductivity being one of them as this is critical in the design of systems employing these materials. The present work aims at developing a novel experimental technique for the simultaneous estimation of principal thermal conductivities of a layered honeycomb composite widely used in aerospace structures. A new standard test material exhibiting structural anisotropy with respect to thermal transport is first conceptualised, designed and fabricated. A full scale direct numerical simulation is performed on the standard test material to understand the thermal transport process in it and determine its principal thermal conductivities. Following this, carefully designed experiments are performed on the standard test material in simulated space environment (inside a vacuum chamber) and its principal thermal conductivities are estimated using the developed inverse methodology based on a synergistic combination of artificial neural network (ANN) and genetic algorithm (GA). Experimentally obtained thermal conductivities are compared with those obtained from full scale numerical simulations. A close agreement between the experimentally and numerically estimated thermal conductivities is observed, validating the technique and establishing the possibility of use of a full scale numerical model as an alternate and standalone

So here you can see this publication which that I was referring to by Samarjeet Chanda, professor c Balaji, professor S P Venkateshan and this work was done at IIT Madras a few years ago. professor c Balaji of course is a distinguished professor also at IIT Madras in the mechanical department and professor SPV S P Venkateshan was also an ex-professor here he is now retired. I think Samarjeet Chanda I am not sure if he is a faculty member at IIT Palakkad but he was at IIT Madras and the PhD student at the time that he wrote this paper this is just a simple demonstration of how you can use ANNs very effectively in order to solve for inverse problems the problem somewhat similar to the one that I described the geometry is a little bit simpler.

But as you can see the abstract here, this is basically the idea is to define or determine the thermal properties of a composite material. The typical composite material here would be the assumption that is you are going to use it for aerospace or satellite applications which is why a person from ISRO was also a joint author in this paper. So, the idea was to determine both an experimental technique as well as an inverse estimation technique I am not going to go over the experiment you are welcome to look at the paper and search for this paper the title is available right here for you it was published in this reputed journal for IJDS, International Journal of Thermal Sciences Professor C Balaji is currently an editor distinguished editor of this journal.

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ificial
ithm
tion

$\hat{T} = w_0 + w_1 x$

$\boxed{\text{Surrogate Model}}$

GA → inverse optimization problem

Gradient Descent/Gauss Newton

So, what was done was the property of a particular honeycomb composite, composite being for the purposes of this video simply being something where you are going to have different anisotropic properties in each direction okay. In such a property you basically want to determine the thermal conductivities. So, they did the full scale direct numerical simulation which I did not go over here in order to understand the thermal transport process and determinates thermal conductivity. So, this is a ground truth for thermal conductivities but let us not look at that. so now all they did was they developed an inverse methodological underlined this okay so the idea here was it required two different algorithms one was an ANN and a genetic algorithm.

This ANN is used as I said just now as a surrogate model, what is meant by a surrogate model, I just explained it, in case you want to run the forward pass really fast you want to approximate the CFD results really fast in order to estimate the property. The genetic algorithm is what was used in order to estimate the optimization problem, the optimization problem or the inverse optimization problem I will come to this distinction later I often find that the first-time people look at it they are a little bit confused even though we have done exactly the same thing so far. So another way of looking at it is the ANN was used to serve the role of remember we had our expression like T-hat equal to w0 plus w1 x instead of that we use an ANN, because We actually do not know the analytical expression we use an ANN there.

So that is the role of the ANN. ANN was serving the role of the forward model now when we do the correction when we do the optimization GA was used to use the same thing as what we used gradient descent for okay gradient descent or gauss newton instead of that a different algorithm was used here, which is the genetic algorithm. So, when you see genetic algorithm just assume that we are doing something like Levenberg Marquardt that Tikhonov regularization of gauss newton so those are the two relative the roles of these two things.

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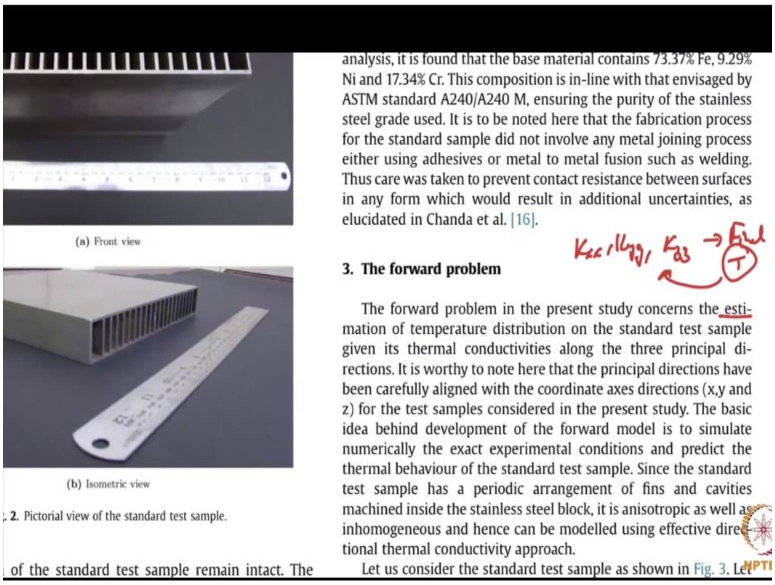

analysis, it is found that the base material contains 73.37% Fe, 9.29% Ni and 17.34% Cr. This composition is in-line with that envisaged by ASTM standard A240/A240 M, ensuring the purity of the stainless steel grade used. It is to be noted here that the fabrication process for the standard sample did not involve any metal joining process either using adhesives or metal to metal fusion such as welding. Thus care was taken to prevent contact resistance between surfaces in any form which would result in additional uncertainties, as elucidated in Chanda et al. [16].

(a) Front view

(b) Isometric view

2. Pictorial view of the standard test sample.

of the standard test sample remain intact. The

3. The forward problem

The forward problem in the present study concerns the estimation of temperature distribution on the standard test sample given its thermal conductivities along the three principal directions. It is worthy to note here that the principal directions have been carefully aligned with the coordinate axes directions (x,y and z) for the test samples considered in the present study. The basic idea behind development of the forward model is to simulate numerically the exact experimental conditions and predict the thermal behaviour of the standard test sample. Since the standard test sample has a periodic arrangement of fins and cavities machined inside the stainless steel block, it is anisotropic as well as inhomogeneous and hence can be modelled using effective directional thermal conductivity approach.

Let us consider the standard test sample as shown in Fig. 3. Let

So, I will just come down here and show you where the forward problem is. so, what we were looking at is design of an isotropic material of this sort and try to estimate the temperature distribution on the standard test sample okay. so, the forward problem here is remember given k_{xx}, k_{yy}, k_{zz} find T so that is what is written here remember the inverse problems given T find k_{xx}, k_{yy}, k_{zz}. so, we are going the other way around in the forward problem so as it is written here you want to estimate the temperature distribution given its thermal conductivities along the three principal directions okay so the standard test sample is shown there

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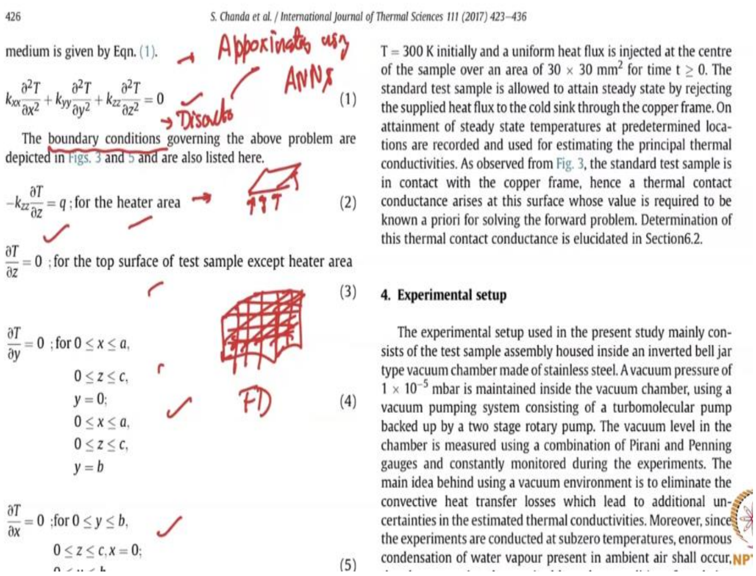

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medium is given by Eqn. (1).

$$k_{xx}\frac{\partial^2 T}{\partial x^2}+k_{yy}\frac{\partial^2 T}{\partial y^2}+k_{zz}\frac{\partial^2 T}{\partial z^2}=0 \quad (1)$$

The boundary conditions governing the above problem are depicted in Figs. 3 and 5 and are also listed here.

$$-k_{zz}\frac{\partial T}{\partial z}=q \text{ ; for the heater area} \quad (2)$$

$$\frac{\partial T}{\partial z}=0 \text{ ; for the top surface of test sample except heater area} \quad (3)$$

$$\frac{\partial T}{\partial y}=0 \text{ ; for } 0\le x\le a,\ 0\le z\le c,\ y=0;\ 0\le x\le a,\ 0\le z\le c,\ y=b \quad (4)$$

$$\frac{\partial T}{\partial x}=0 \text{ ; for } 0\le y\le b,\ 0\le z\le c, x=0; \quad (5)$$

T = 300 K initially and a uniform heat flux is injected at the centre of the sample over an area of 30 × 30 mm^2 for time t ≥ 0. The standard test sample is allowed to attain steady state by rejecting the supplied heat flux to the cold sink through the copper frame. On attainment of steady state temperatures at predetermined locations are recorded and used for estimating the principal thermal conductivities. As observed from Fig. 3, the standard test sample is in contact with the copper frame, hence a thermal contact conductance arises at this surface whose value is required to be known a priori for solving the forward problem. Determination of this thermal contact conductance is elucidated in Section6.2.

4. Experimental setup

The experimental setup used in the present study mainly consists of the test sample assembly housed inside an inverted bell jar type vacuum chamber made of stainless steel. A vacuum pressure of 1 × 10^{-5} mbar is maintained inside the vacuum chamber, using a vacuum pumping system consisting of a turbomolecular pump backed up by a two stage rotary pump. The vacuum level in the chamber is measured using a combination of Pirani and Penning gauges and constantly monitored during the experiments. The main idea behind using a vacuum environment is to eliminate the convective heat transfer losses which lead to additional uncertainties in the estimated thermal conductivities. Moreover, since the experiments are conducted at subzero temperatures, enormous condensation of water vapour present in ambient air shall occur, And of course the equations are the same as what I showed earlier k xx del square T del x square plus k yy del square T del y square etcetera and you are also given the boundary conditions so which are of course essential in estimating the forward problem.

Otherwise, you cannot really solve the forward problem so you have insulation at a few ends you have and this place you have a free conductive boundary and here of course is insulation and this is at the bottom side you are providing some bead so these details are unimportant as far as the course is concerned, but you can see the detail to which you need to give the model perfectly in order for you to solve it. now if I gave you this analytically, I can give you all these things a b c and ask you to solve analytically, you cannot solve it analytically, because this is not something that you can easily solve you will have to use some Fourier series and even then, frankly you will get only a few terms.

So, what we do is effectively what we are doing is approximating using ANNs. Now there are two ways of approximating using ANNs, the first way to approximate using ANNs is solve the CFD solution okay so that is what is done you now discretize this this is called turn it into discrete sets, which means you have this box. you put lots and lots of meshes okay you put three d meshes and at all these points you write a discrete version of the finite difference equation and you solve a linear system of equations, that is going to be a big linear system and it is going to be an expensive solution. once you solve this then you approximate it so you make a table of various solutions so basically what they did was for various values of k_{xx}, k_{yy}, and k_{zz}, they ran for various x, y, z.

How they solved this problem and measured at various x y zs made a giant data table as far as I know they ran two hundred simulations I will show you that later in the paper, they ran two hundred simulations collected all that data and then approximated this data using ANNs and we saw the process of approximation in great detail in the previous weeks so once you approximate that then you go ahead and solve the inverse problem. but first let us see the forward problem and how we approximated using ANN.

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with test sample at z = c

$$\frac{\partial T}{\partial z} = 0 \text{ ;for the bottom of test sample at } z = c, \text{ except the copper frame area} \quad (7)$$

The standard test sample is at a uniform temperature of

throughs essentially consist of two mating parts both having metal contact pins on either side. The electrical and thermocouple wires are soldered both on to the inner(vacuum side) and outer (open atmosphere) side pins of the mating contact parts of the feed-through. Once both the push on type mating parts of the feed-through are connected the circuit gets completed and electrical and voltage signals are transferred from inside the vacuum chamber to

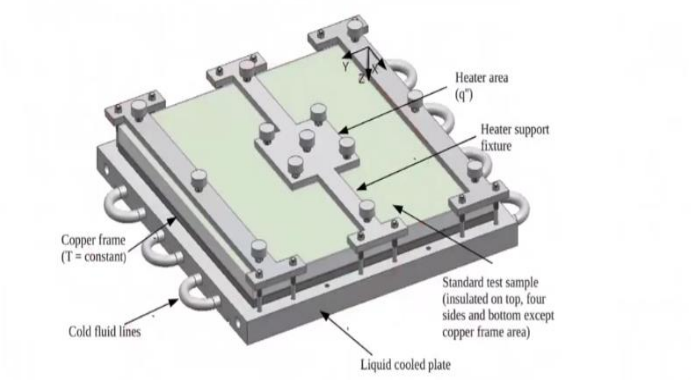

Fig. 3. Assembled view of the standard test sample setup.

So, this is what the setup looks like, the actual physical setup.

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ched foil heater a direct current (DC) power
regulated and programmed as well to give a
to the heater in order to control the heater
e the heat flux injected into the test sample.
components of the test sample and associ-
in Fig. 4. The measurement data is acquired
el data acquisition system (EX1048A) man-
uments. The instrument has a resolution of
programmable and can be connected to a
og the data into files during the experiments
the experimental setup, one may refer to
e temperatures at the predetermined loca-
the data acquisition system at steady state
when none of the temperatures changes by
) and are used for the estimation of principal
by harnessing the inverse model using a
chnique.

m

rincipal thermal conductivities namely k_{xx},
easured steady state temperature distribu-
f the inverse problem being solved in the
se problems in general are formulated in
"causes"from the "effects"and are ill posed

layer. Using artificial neural networks one can simulate a complex non linear relation between the independent and dependent variables as linear ones successively, each hidden layer being responsible for accomplishing the same.

$\hat{T} = w_0 + w_1 x$

The finite difference solution to the forward problem is transformed into a feed forward back propagation Artificial Neural Network and is trained using the Levenberg Marquardt algorithm. Such an exercise leads to a reduction of computational cost as elaborated by Chanda et al. [16] The network has one hidden layer with 20 neurons, takes k_{xx}, k_{yy} and k_{zz} as input and yields 19 temperatures as output. A total of 200 data sets of temperatures and corresponding $1 \leq k_{xx}, k_{yy}$ and $k_{zz} \leq 15$ W/mK are used for training the network. The Genetic algorithm code available with MATLAB software has been used in the present study. The entire process as elucidated above is depicted in the form of a flowchart in Fig. 6 The various Genetic algorithm input parameters used are listed in Table 2. For an elaborate discussion on Genetic algorithms please refer to Goldberg [17].

6. Estimation of principal thermal conductivities of standard test sample

The detailed analysis undertaken for estimation of principal thermal conductivities of the standard test sample is presented in this section with emphasis on estimation of thermal parasitic losses

Now I will show you where they measured it also this directly jumps into the inverse problem but I before I come there you can see this the finite difference of the forward problem is transformed into a feed forward back propagation or artificial neural network.

So, this is where so you can see that even this ANN can be used, we use gradient descent but they used Levenberg Marquardt so forget that. what this is doing is a simple thing you are basically trying to find out the equivalent of $\hat{T} = w_0 + w_1 x$ but the way you do that is take the finite different solution run many different solutions how many they took two hundred data sets for various values of k_{xx}, k_{yy}, k_{zz} made a giant table, I will show you some examples of some small tables in the next week but they made a giant table and all they did was they put a one hidden layer now they approximate the result of this all these data collected using just twenty neurons turns out that is sufficient which is remarkable actually.

But for this range it turns out it was just sufficient to run with this simple case okay so once they did that, they now have a full ann. once you do that you actually can now estimate the principal thermal conductivities of the test sample okay now how do they do that.

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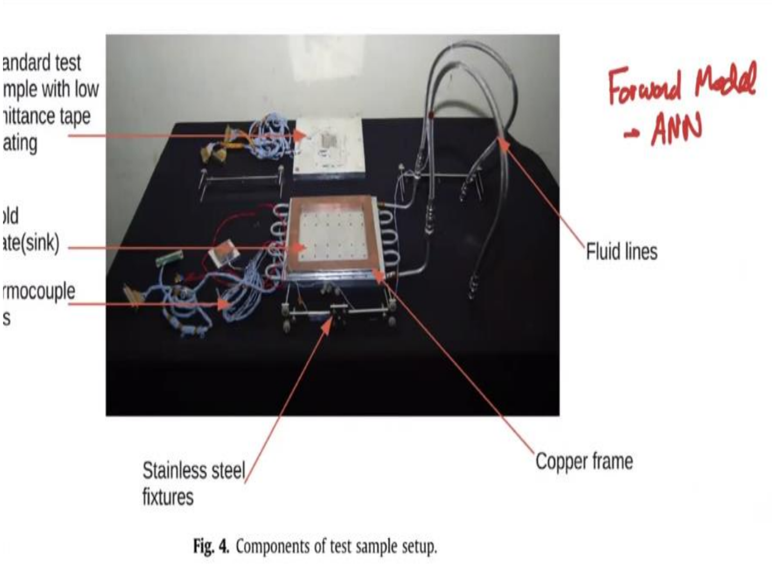

you see here is the setup we actually now have a forward model they did something slightly clever with the forward model compared to what I said but let us forget that they took a forward model and the forward model is the ann. now forget the ANN for now. now only assume that you have the forward model how do we solve the inverse problem?

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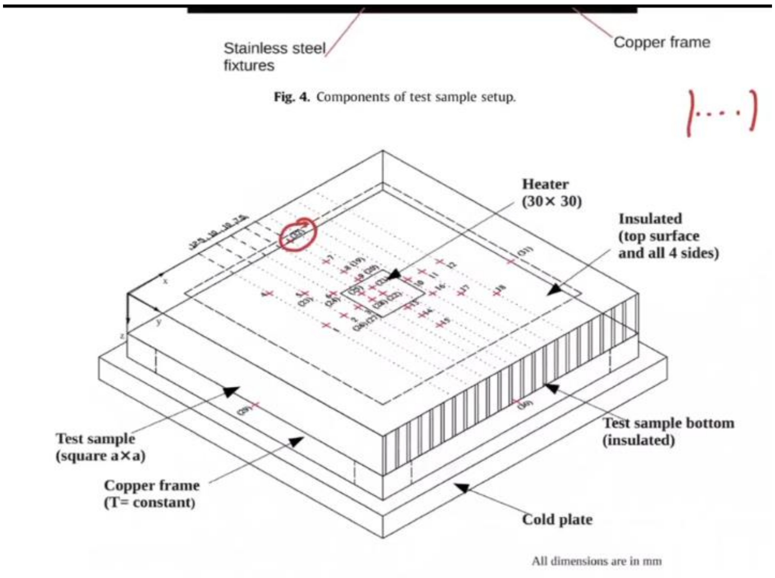

We actually now have to measure temperatures just like in our slab problem we were measuring six temperatures here they measured you can see up to thirty-two temperatures okay. so let us say thirty-two temperatures or nineteen temperatures or something around that okay. So, they measure around nineteen to thirty-two temperatures I think I might be wrong or it might be nineteen temperatures or so they measured a certain number of temperatures

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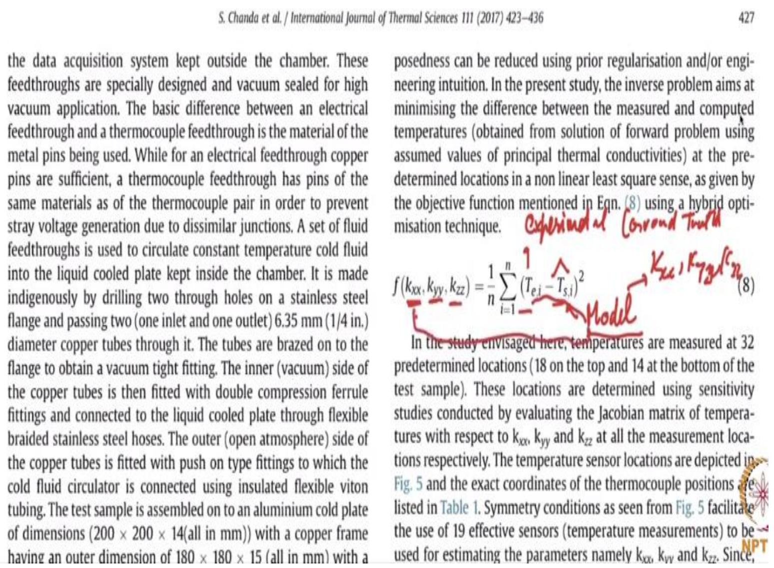

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the data acquisition system kept outside the chamber. These feedthroughs are specially designed and vacuum sealed for high vacuum application. The basic difference between an electrical feedthrough and a thermocouple feedthrough is the material of the metal pins being used. While for an electrical feedthrough copper pins are sufficient, a thermocouple feedthrough has pins of the same materials as of the thermocouple pair in order to prevent stray voltage generation due to dissimilar junctions. A set of fluid feedthroughs is used to circulate constant temperature cold fluid into the liquid cooled plate kept inside the chamber. It is made indigenously by drilling two through holes on a stainless steel flange and passing two (one inlet and one outlet) 6.35 mm (1/4 in.) diameter copper tubes through it. The tubes are brazed on to the flange to obtain a vacuum tight fitting. The inner (vacuum) side of the copper tubes is then fitted with double compression ferrule fittings and connected to the liquid cooled plate through flexible braided stainless steel hoses. The outer (open atmosphere) side of the copper tubes is fitted with push on type fittings to which the cold fluid circulator is connected using insulated flexible viton tubing. The test sample is assembled on to an aluminium cold plate of dimensions (200 × 200 × 14(all in mm)) with a copper frame having an outer dimension of 180 × 180 × 15 (all in mm) with a

posedness can be reduced using prior regularisation and/or engineering intuition. In the present study, the inverse problem aims at minimising the difference between the measured and computed temperatures (obtained from solution of forward problem using assumed values of principal thermal conductivities) at the predetermined locations in a non linear least square sense, as given by the objective function mentioned in Eqn. (8) using a hybrid optimisation technique.

Experimental (Ground Truth)

$$f(k_{xx}, k_{yy}, k_{zz}) = \frac{1}{n}\sum_{i=1}^{n}(T_{e,i} - \hat{T}_{s,i})^2 \quad (8)$$

Model → K_{xx}, K_{yy}, K_{zz}

In the study envisaged here, temperatures are measured at 32 predetermined locations (18 on the top and 14 at the bottom of the test sample). These locations are determined using sensitivity studies conducted by evaluating the Jacobian matrix of temperatures with respect to k_{xx}, k_{yy} and k_{zz} at all the measurement locations respectively. The temperature sensor locations are depicted in Fig. 5 and the exact coordinates of the thermocouple positions are listed in Table 1. Symmetry conditions as seen from Fig. 5 facilitate the use of 19 effective sensors (temperature measurements) to be used for estimating the parameters namely k_{xx}, k_{yy} and k_{zz}. Since,

Now all you need to do is to say that I want my model I want my model parameters I want k_{xx}, k_{yy}, k_{zz} such that T estimated is different from the ground truth so T simulated basically is the ground truth and T estimated is whatever we are predicting the temperature to be for this k_{xx}, k_{yy}, k_{zz} okay.

So, the ground truth is the x sorry I think I used the notations wrong T e in this paper this is why it is important to know is experimental which is the ground truth and we have simulated is actually our estimate or what we call T-hat. so I just call it T-hat here just for your clarity so you actually take the experimental temperature and then you take your model and ensure that the two of them are as close by as possible now how do we do the model we already know that for the model if I give k_{xx}, k_{yy}, k_{zz} it can give me an estimate okay so once you give an estimate compare it with the actual experiment if that does not work out correct the model. Now it is for this correction that they use genetic algorithms.

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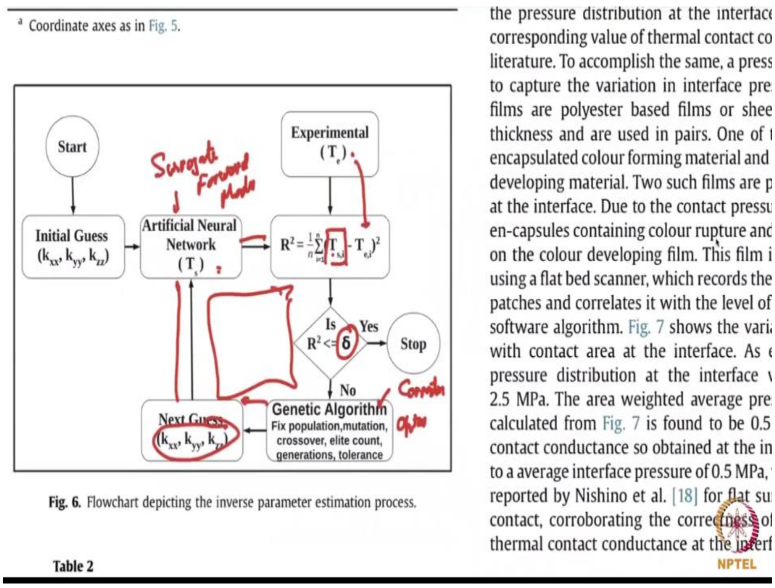

So here is the whole flowchart, you start you give some guess this you will see is the standard inverse process you have a trained artificial neural network once again I will emphasize this is simply a surrogate forward model. If you had huge computer power you do not need an ANN okay all you need to do is run the full CFD okay if you do not want to run the CFD you run an ANN you run the ANN, this ANN gives you T s you have experiments okay. you just conducted the experiment that gives you T e. now once this does not match if it is not lesser than a specific error that we want then you correct so GA the genetic algorithm is for correction basically for optimization so forget all that because we did not do genetic algorithms here but sufficient to say genetic algorithms are basically just an optimization algorithm.

Instead of gauss newton or gradient descent you use genetic that generates the next guess just like we had w equal to or k xx would be equal to k xx minus alpha del j del k xx instead of that genetic algorithm has a different way of getting there then next guess goes to the ANN and it goes here and you keep on going in the cycle till you get some optimal k_{xx}, k_{yy}, k_{zz}. so, in this video we saw that a family practical problem and this can be utilized in various practical problems. you can actually use ANNs as a substitute in order to instead of simulations in order to guess the forward model, you can use ANNs to guess the forward model. as I said I will show you a very simple example of this in the next weeks simulation.

But this is the best that we can do it turns out you can do something even more clever which is where we come to physics informed neural networks and I will demonstrate that or I will talk about that in the next week or next video thank you.